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A Novel Approach for Measuring Electrical Impedance Tomography for Local Tissue with Artificial Intelligent Algorithm

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Abstract

This paper proposes a novel approach for measuring Electrical Impedance Tomography (EIT) of a living tissue in a human body. EIT is a non-invasive technique to measure two or three-dimensional impedance for medical diagnosis involving several diseases. To measure the impedance value electrodes are connected to the skin of the patient and an image of the conductivity or permittivity of living tissue is deduced from surface electrodes. The determination of local impedance parameters can be carried out using an equivalent circuit model. However, the estimation of inner tissue impedance distribution using impedance measurements on a global tissue from various directions is an inverse problem. Hence it is necessary to solve the inverse problem of calculating mathematical values for current and potential from conducting surfaces. This paper proposes a novel algorithm that can be successfully used for estimating parameters. The proposed novel hybrid model is a combination of an artificial intelligence based gradient free optimization technique and numerical integration. This ameliorates the achievement of spatial resolution of equivalent circuit model to the closest accuracy. We address the issue of initial parameter estimation and spatial resolution accuracy of an electrode structure by using an arrangement called "divided electrode" for measurement of bio-impedance in a cross section of a local tissue.

Keywords: Artificial Intelligence, Alopex Algorithm, Divided Electrode Method, Electrical Impedance Tomography, Equivalent Circuit Model, Medical Imaging

1. INTRODUCTION

Biological tissues have complex electrical impedance related to the tissue dimension, the internal structure and the arrangement of the constituent cells. Therefore, the electrical impedance can provide useful information based on heterogeneous tissue structures, physiological states and functions [1, 2]. In addition the concepts of time varying distribution of electrical properties inside a human body such as electrical conductivity and (or) permittivity can be used to analyze a variety of medical conditions. High-conductivity materials allow the passage of both direct and alternating currents and high-permittivity materials allow the passage of only alternating currents. Both of these properties are of interest in medical systems since different tissues have different conductivities and permittivities [3, 4].

In an effort to obtain more precise evaluations of tissues for diagnostic purposes, bio-impedance measurements can be focused on specific local tissues such as tumors, mammary glands and subcutaneous tissues [5]. Most importantly tissue impedance at zero frequency, corresponding to extra cellular resistances is particularly useful for evaluating mammary glands, lung cancers and fatty tissues [6, 7, 8]. In comparison with x-ray images, ultrasonic images and magnetic resonance imaging (MRI), electrical impedance measurement is inexpensive.

A variety of medical systems such as X-ray, CT, MRI and Ultrasonic Imaging are used for medical tissue diagnosis. These systems create a two-dimensional (2D) image from the information based on density distribution of the living tissue. On the other hand, EIT (also called Applied Potential Tomography) creates a two-dimensional image from information based on the impedance characteristics of the living tissue. This information acquired through EIT can be clinically very useful. For example, in order to obtain precise evaluations of tissues for diagnostic purposes, bio-impedance measurements can be focused on the specific local tissues such as tumors, mammary glands and subcutaneous tissues [5]. Additionally, EIT could be extremely convenient in several medical conditions requiring bedside therapies such as Pulmonary Oedema, Cerebral Haemorrhage and Gastric Emptying among others. Typically, conducting electrodes are attached to the skin of the subject and small alternating currents are applied to some or all the electrodes in a traverse plane. These are linked to a data acquisition unit, which outputs data to a computer. By applying a series of small currents to the body, a set of potential difference measurements can be recorded from non-current carrying pairs of electrodes.

When it comes to practical implementation of EIT, there are several limitations such as the complicated spatial distribution of the bio-impedance that arises from complex structure of biological tissues, in addition to the structure and arrangement of measurement electrodes. To obtain reasonable images, at least one hundred, and preferably several thousand, measurements are usually carried out. This results in relatively long time for measuring and analyzing specifically, due to changing combination of pair of electrodes. Therefore, in many instances, it is difficult to achieve high precision and to assert measurement results as clinically relevant information.

In order to overcome this drawback, there is a need to address several issues for employing EIT in medical application such as, estimating impedance parameters for local tissue (i.e. inner tissue impedance distribution) and the shape of electrode structure. In this paper, we address the issue of electrode structure by using an arrangement called “Divided Electrode” for measurement of bio-impedance in a cross section of a local tissue. The determination of local impedance parameters can be carried out using an equivalent circuit model. However, the estimation of inner tissue impedance distribution using impedance measurements on a global tissue from various directions is an inverse problem. Hence it is necessary to solve the inverse problem of calculating mathematical values for current and potential from conducting surfaces. Experiments were then conducted by using two different algorithms, Newton Method and Alopex method for determination of impedance parameters in the equivalent circuit model. Newton method is deterministic since it uses steepest descent approach while Alopex is a stochastic paradigm.

Experimental results show that, higher accuracy can be obtained while estimating the parameter values with Newton method. However, selecting an appropriate set of initial parameters with Newton method is highly complicated and is based on trial and error. This translates into a leading disadvantage in the effectiveness of Newton method. Since Alopex is a stochastic approach it is able to seek out the global minima using any arbitrary set of parameter values. However it takes several iterations and often converges on a near optimum solution rather than the precise parameter values. Therefore, to obtain results with appropriate initial parameters with high accuracy, simulations were carried out using a novel approach, which relies on stochastic approach initially and then uses deterministic calculations to obtain the final parameter values with a high accuracy. Thus, the novel method overcomes the distinct disadvantage of each of the methods. Overall this ameliorates the performance of spatial resolution of equivalent circuit model to the closest accuracy.

2. BACKGROUND

EIT system primarily comprises of the electrodes attached to a human body, a data acquisition unit and an image reconstruction system. Voltage is measured through data acquisition system, which is then passed to another system for reconstruction the image [9]. The goal here is to distinguish various tissue types. This is possible because the electrical resistivity of different body tissues varies widely from 0.65 ohm-m from cerebrospinal fluid to 150 ohm-m for bone. T. Morimoto and Uyama, while studying the EIT for diagnosis of pulmonary mass emphasized that the electrical properties of biologic tissues differ depending upon their structural characteristics and differences in the electrical properties of various neoplasms [10]. As impedance is an important electrical property, intra operative impedance analysis can be used to measure the impedance of pulmonary masses, pulmonary tissues, and skeletal muscle [5].

The first impedance imaging system was the impedance camera constructed by Henderson and Webster [11]. This system used a rectangular array of 100 electrodes placed on the chest that were driven sequentially with a 100 kHz voltage signal. A simple conductivity contour map was produced based on the assumption that current flows in straight lines through the subject. This was one of the initial efforts towards practical implementation of EIT technology in a medical system. In [47], Agarwal et al. have discussed the novel approach medical image reorganization with GMDH algorithm.

In the early eighties, Barber and Brown constructed a relatively simple yet elegant EIT system using 16 electrodes by applying the constant amplitude current at 50 kHz between two electrodes at a time [12]. Ten images per second were generated, which were computed using back-projection. This method has been applied with great success in the field of X-ray tomography. The image depicted the structure of bones, muscle tissue, and blood vessels. However, the resolution of the image was very low. This image is generally regarded as the first successful vivo image generated by an EIT system.

There are mainly two methods in EIT that have been explored in depth: 2-D EIT and 3-D EIT. Commonly, 2D EIT systems could be divided into two different category sets namely: Applied Potential Tomography (APT) and Adaptive Current Tomography (ACT). In 2-D EIT system electrodes are positioned at an equal spacing around the body to be imaged thus, defining a plane through the object. Images are then reconstructed assuming that the data were from a 2-D object. These objects mainly demonstrate a significant amount of contribution to the image from off-plane conductivity changes. It further implies that unlike in any 3D X-ray image that can be constructed from a set of independent 2-D images, for 3D EIT it is necessary to reconstruct images from data collected over the entire surface of the object volume [13]. Metherall, et al, 1996, researched the impact of off-plane conductivity changes on to the reconstructed image in 2-D EIT. Metherall et al, [14] further studied 2D EIT and used these observations to further carry out comparisons between 2D and 3D EIT. They produced the images using a 16-electrode system with interleaved drive and receive electrodes [15]. With the 3-D methods, the reconstructed images are more accurate as compared to original images. Lionheart et al [16] constructed a 3D EIT image at Oxford Brookes University. They constructed a time average EIT image of cross section of a human chest. For constructing a 3-dimensional (3D) EIT image, conducting electrodes were attached around the chest of a patient. The lungs were presented as a low conductivity region. The resulting image was a distorted image as a 2D reconstruction algorithm was employed instead of a 3D reconstruction algorithm [17].

2.1 Challenges in EIT

There are few issues that need to be addressed for implementing EIT in practical medical systems: (1) the complicated spatial distribution of the bio-impedance that arises from obscure structure of biological tissue; (2) the structure and arrangement of measurement electrodes.

In EIT realm for local tissue a new simulation method was introduced which is a combination of divided electrodes and guard electrodes [18]. In this method required data are obtained by one time measurement. In this paper, we evaluate the efficiency of the new method by computer simulations, where a typical multilayer tissue model composed of skin, fat, and muscle is used. As an example, conductivity distribution in a cross section of the local tissue is estimated using the resistances measured by the divided electrodes. Tissue structures are also estimated simultaneously by increasing the number of the divided electrodes.

Estimation of inner tissue impedance distribution using impedance measurements on a global tissue from various directions is an inverse problem. This results in relatively long time for measuring and analyzing especially due to changing combination of pair of electrodes. There are various concerns that need to be addressed for implementing and deploying EIT system in a real world scenario as a medical imaging system. This includes estimating parameters and electrode structure. Therefore, in many instances, it is difficult to achieve high precision and exactly define the measurement result as clinically relevant information.

2.2 EIT Applications

In EIT imaging, significant alterations in interior properties could result only in minor changes in the measurements [19], implying that it is nonlinear and is extremely ill posed in its behavior resulting the need for high-resolution image measurements with very high accuracy. Thus, converting EIT principles into a commercial application is a challenging process.

There are two main methodologies that have addressed this issue: Applied Potential Tomography (APT) system and Adaptive Current Tomography (ACT) system. APT was developed by Barber and Brown in Sheffield, England [20]. APT system has been successfully employed in the research of various physiological processes, such as blood flow in the thorax, head, and arm, pulmonary ventilation and gastric emptying. ACT was developed at Rensselaer Polytechnic Institute. ACT method has been employed to produce images of the electrical conductivity and permittivity in the human thorax, and breast studies. EIT techniques can be applied to a medical system for acquiring constructive information. This results in various applications [21].

Breast Imaging Using EIT [22, 23]**:** In [46] Ahmed el. al. have provided a detailed review about breast cancer prognosis. X-ray mammography is the standard imaging method used for early detection of breast cancer. However, this procedure is extremely uncomfortable and painful for most women. The high cost of the system forbids its widespread use in developing countries. In addition, the ionizing radiation exposure is damaging to the breast tissue and its harmful effects are cumulative. This method further suffers from high percentages of missed detection and false alarms resulting in fatalities and unnecessary mastectomies.

On the other hand, EIT is an attractive alternative modality for breast imaging. The procedure is comfortable; the clinical system cost is a small fraction of the cost of an X-ray system, making it affordable for widespread screening. The procedure further poses no safety hazards and has a high potential for detecting very small tumors in early stages of development [24]. Hartov et al. at Dartmouth constructed and analyzed a 32-channel, multi-frequency 2D EIT systems. Newton's method was the base for the image construction [25]. Osterman et al. further modified the Dartmouth EIT system in a way, so as to make it feasible for routine breast examinations [26]. More efforts were later put in, in order to achieve more consistency of the results with an improved breast interface [24].

EIT in Gastrointestinal Tract: EIT images of the lungs and gastrointestinal system were published in 1985 [27]. Studies were undertaken to assess the accuracy of the gastric function images and good correlation with other methods was obtained. Experiments were also undertaken to assess the system's use for monitoring respiration, cardiac functions [28], hyperthermia [29], and intra-ventricular haemorrhage in low-birth weight neonates. This study established that, citrate phosphate buffers can be used as an alternative test liquid for EIT monitoring, and that pH has a systematic effect on gastric emptying and the lag phase [30].

Hyperthermia: In 1987 in vitro and in vivo studies were carried out to determine the feasibility of imaging local temperature changes using EIT to monitor hyperthermia therapy [31]. EIT may be used for temperature monitoring because tissue conductivity is known to change with temperature. Malignant tumors might be treated by artificially increasing temperature by microwave radiation or lasers.

3. EQUIVALENT CIRCUIT MODEL

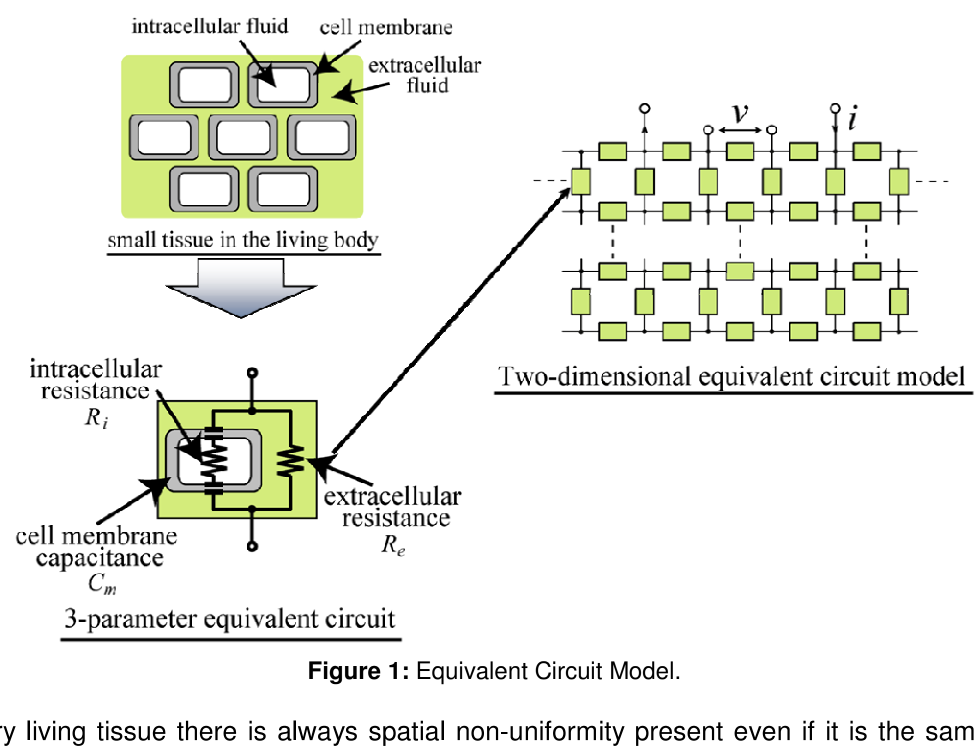

Figure 1: Equivalent Circuit Model.

In every living tissue there is always spatial non-uniformity present even if it is the same tissue such as muscular or hepatic tissue. The presence of this non-uniformity within the living tissue can be determined by using either the Cole-Cole distribution [32] or the Davidson-Cole distribution [33] to estimate the distribution of the time constant (electric relaxation time) of the circuit model. In this research, impedance distribution in the tissue cross section is represented by a 2D distributed equivalent circuit model as shown in Figure 1.

This spatial distributed equivalent circuit is used to model at individual cell or small tissue level. Therefore, it reflects the impedance spatial distribution. In other words, each small tissue is expressed as an equivalent circuit, which can be expressed using three parameters, namely, the intracellular and extracellular resistances denoted as Ri and Re respectively, and cell membrane capacitance denoted as Cm. In this model, equivalent circuits with three parameters are connected in the shape of a lattice. The electrodes used to measure v and i are assumed to be point electrodes.

4. DIVIDED ELECTRODE METHOD

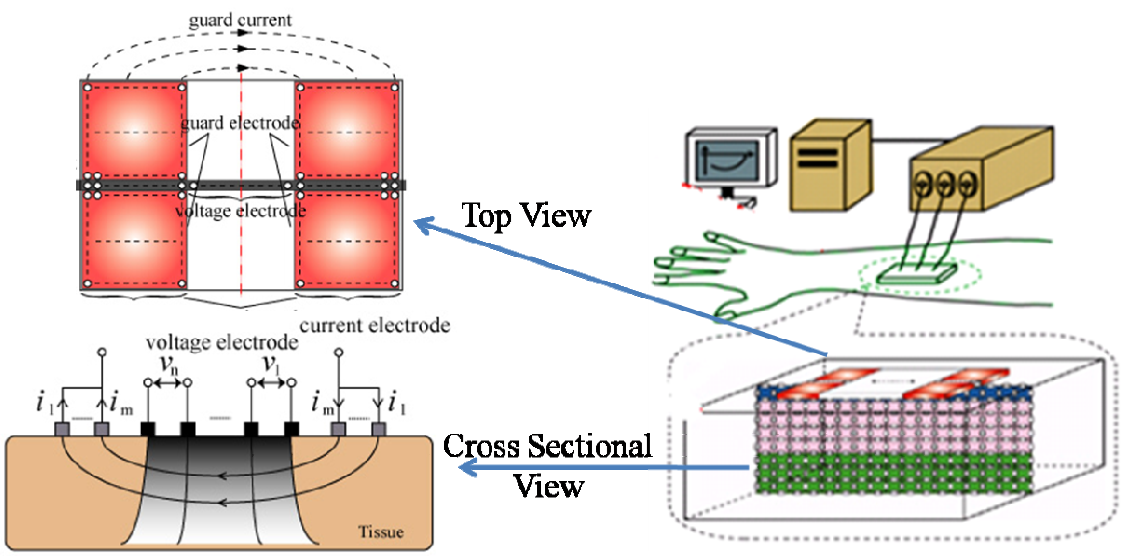

FIGURE 2: Experimental setup for Divided Electrode Method for Impedance Measurement.

The divided electrode method for impedance measurement, which was used in this study, is shown in Figure 2. The figure also shows the top view and the cross sectional view of the divided electrode arrangement. This type of electrode is referred to as divided electrode because it has a shape of a plate, which is divided by slits.

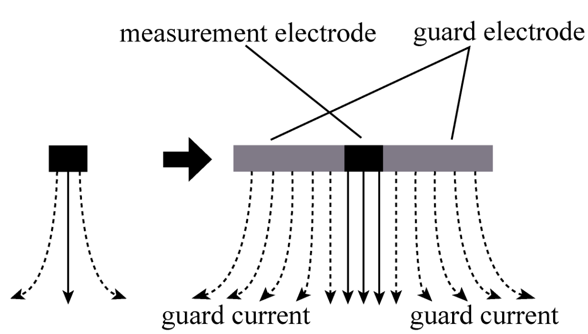

FIGURE 3: Placement of Guard Electrodes on Both Sides of the Current Electrode.

Note that the current electrodes are arranged on both sides of the voltage electrode, which is located in the centre. The current flows simultaneously from all the current electrodes. To control the flow of the current, a guard electrode is placed around each current electrode. Figure 3 shows this arrangement.

Due to the presence of this guard electrode the current from the current electrode flows right into the cross section without spreading. This allows us to measure the value of the 2D impedance distribution [34, 35]. The current electrodes control the measuring range in the direction of depth while the voltage electrodes are employed for controlling the measuring range in the direction of the electrode-axis. Therefore, the number of impedance values obtained at once is given by {m×n} where m is the number of current electrodes (i1,i2,…,im) and n is the number of voltage electrodes (v1,v2,…,vn). This allows one to obtain high-resolution measurements at a high-speed.

5. ESTIMATION METHOD

Figure 4 shows the system model for the proposed novel approach. As shown in the Figure 4, the proposed noble approach, we use the Alopex algorithm – a stochastic approach, to determine the initial set of parameter values. Later, deterministic calculation (Newton's method) is applied to calculate the final set of parameters with high accuracy and precision.

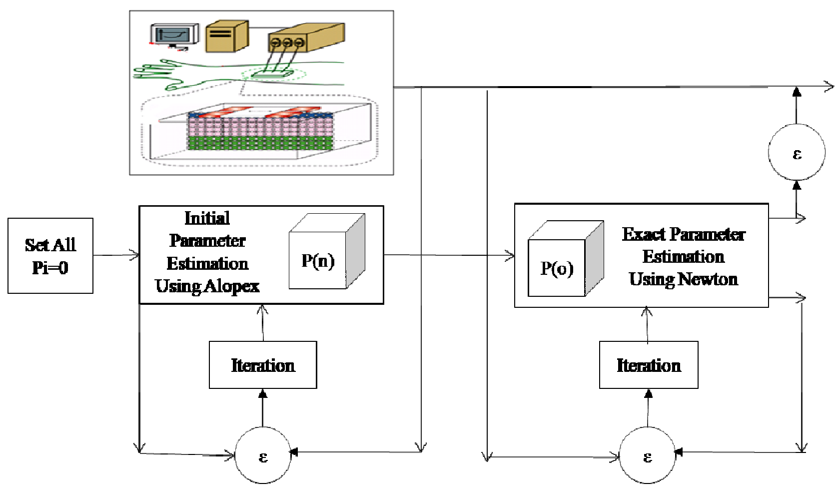

Figure 4: System Model for the Proposed Novel Approach.

5.1 Alopex Algorithm

Alopex (Algorithm for Pattern Extraction) is an iterative process [36], which was originally proposed for the study of visual receptive fields of frogs, relied on optimization based on cross-correlations rather than derivatives. Originally the goal of Alopex was to find a visual pattern (an array of light intensities) which maximizes the response from individual neurons in the brain [37, 36, 38]. Later the Alopex algorithm was developed [38, 39] for application to a variety of optimization problems where the relationship between the cost and optimization parameters cannot be mathematically formulated. In 1990 Pandya [39, 40, 41] introduced Alopex as a learning paradigm for multi-layer networks. They claimed their new version of Alopex to be network-architecture independent, which does not require error or transfer functions to be differentiable and has a high potential for parallelism [42]. Since then, many versions of the ALOPEX have been developed [43, 44, 45].

As a generic optimization framework, ALOPEX has certain prominent advantages. It is a gradient free optimization method, totally network architecture independent and provides synchronous learning. These exclusive features make ALOPEX a distinguishable tool for optimization and many machine learning problems [42]. In optimization process, Alopex chooses set of variables, which actually describe the state of the system at any given time. A “cost function” F is derived as a function of these variables. The cost function now acts as a object of the optimization process and represents the degree of the closeness of the system to several possible states, one of which is the desired, in our context it is the ‘error minimization’. At each iteration, the values of these variables get updated and cost function is recalculated. Over several iterations the cost function can be brought to an absolute minimum. This state is referred as “convergence” or “global minimum”. Similarly Artificial Neural Networks have found several applications in medical field [48].

5.2 Mathematical Framework for Novel Approach

In order to evolve a model connecting N equivalent circuits with three parameters as shown in Figure 1 it is necessary to estimate the circuit parameter p. Here p is a vector composed of circuit parameters, Ri, Re and Cm corresponding to N circuits. This is an inverse problem and the p values must be estimated using measured impedance data. Impedance data ZD measured by K electrodes arrangement is expressed as:

$$Z_D(\omega) = [Z_D^{(1)}(\omega), Z_D^{(2)}(\omega), \dots \dots \dots \dots, Z_D^{(K)}(\omega)]^T \qquad (1)$$

The parameter vector p is expressed as:

$$p = [R_e(1), R_i(1), C_m(1), \dots \dots, R_e(N), R_i(N), C_m(N)]^T \qquad (2)$$

The initial value of the parameter p is set to p0. The proposed novel method relies on a stochastic approach during the initial period of estimation and then uses deterministic calculations to obtain the final parameter values with a high accuracy. During the initial stochastic phase the value of the error is calculated using equation 3:

$$\varepsilon = \sqrt{\frac{1}{M}\frac{1}{K}\sum_{i=1}^{M}\sum_{j=1}^{K}\left|\frac{Z^{(j)}(p_o,\omega_i) - Z_D^{(j)}(\omega_i)}{Z_D^{(j)}(\omega_i)}\right|^2} \qquad (3)$$

Where, M, N, K, ZD and ωi denote the number of voltage electrodes, number of current electrodes, number of frequencies, impedance values calculated using the equivalent circuit model, and the value of the frequency respectively. During the initial phase, at the nth iteration the Pi(n) value is calculated as follows:

$$\delta Pi(n) = Pi(n-1) + \delta Pi \qquad (4)$$

where δPi is given by:

$$(\delta Pi(n))$$

Δi(n) = + d with probability P (5)

$$= -d \ with \ probability \ 1 - P(\Delta_i(n))$$

$$\Delta_i(n) = \{p_i(n-1) - p_i(n-2)\}\{\varepsilon(n-2) - \varepsilon(n-1)\}$$

Where is given by, (6)

and the value for P(Δi(n)) is given by:

$$P\left(\Delta_i(n)\right) = \left(\frac{1}{1 - e^{\frac{-\Delta_i(n)}{T}}}\right) \tag{7}$$

In equation 7, T represents the temperature value. Using the p(n) values the corresponding Z(p,ω) value is calculated based on the equivalent circuit model and equation 3 is used to determine the error. Once the value of the error is within the tolerance limit the estimation of p values is switched to a deterministic algorithm. The goal here is to change the value of Z, by changing the value of p so that δZ approaches to zero.

$$\delta Z(p,\omega) = Z_D(\omega) - Z(p,\omega) \tag{8}$$

The mathematical equations for calculating the final value of the error and the estimated parameters are calculated using the following equations:

$$\delta Z(p,w) = \left[\frac{\delta Z(p,\omega)}{\delta p}\right]_{po} \delta p \tag{9}$$

$$b = A\delta p \tag{10}$$

Where the value of A is:

$$A = \left[\left[\frac{\delta Z(p,\omega_i)}{\delta p}\right]_{p0}, \ldots\ldots\ldots, \left[\frac{\delta Z(p,\omega_M)}{\delta p}\right]_{p0}\right]^T \tag{11}$$

Here A is an M×N x K matrix and b is a K-dimensional vector. Substituting the value of A from equation 11 in equation 10, the equation 10 becomes,

$$b = [\delta Z(p,\omega_I)^T, \ldots\ldots, \delta Z(p,\omega_M)^T]^T \tag{12}$$

Z(p,ω) can be obtained using the p values and the equivalent circuit model. Here, A can be obtained from the numerical analysis based on the equivalent circuit model shown in Figure 1. Therefore, calculation of the least squares method of equation 11 is expressed by equation 12 to obtain δp, which denotes the change in the parameter value with respect to the initial value p0.

6. SIMULATION RESULTS

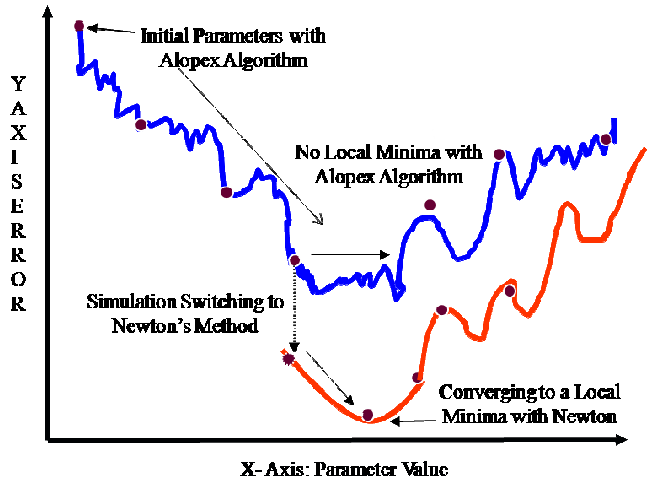

FIGURE 5: Convergence Graph for the Proposed Noble Algorithm.

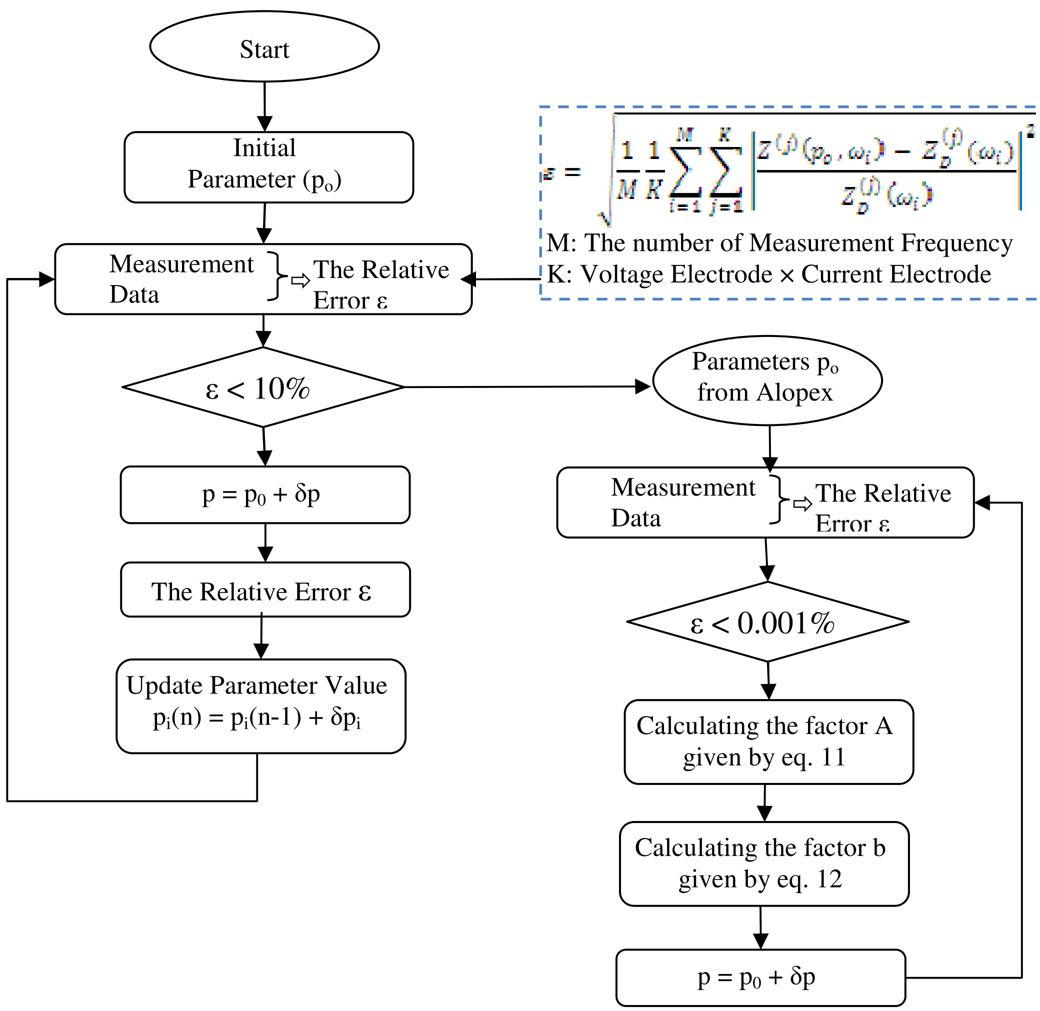

FIGURE 6: Algorithm for the Proposed Novel Approach.

Ideally, a deterministic method likes Newton Method yields quick convergence for inverse problems. However, in this case it was found that Newton method often failed to converge due to the presence of local minima, if the initial parameter set was not reasonably close to the global minimum. Selecting a set of appropriate initial parameters with Newton's method is highly complicated and is based on trial and error. Alopex being a stochastic method takes several iterations (in the order of thousands) to converge. However, it is able to seek out the global minima from any arbitrary set of initial parameters.

Figure 5 shows that the proposed novel approach employs Alopex algorithm for selecting the initial parameter value. Once the error value converges within the acceptable bound, the Newton's method is employed for converging to local minimum. Figure 6 shows a flow chart for the final algorithm for the proposed novel approach.

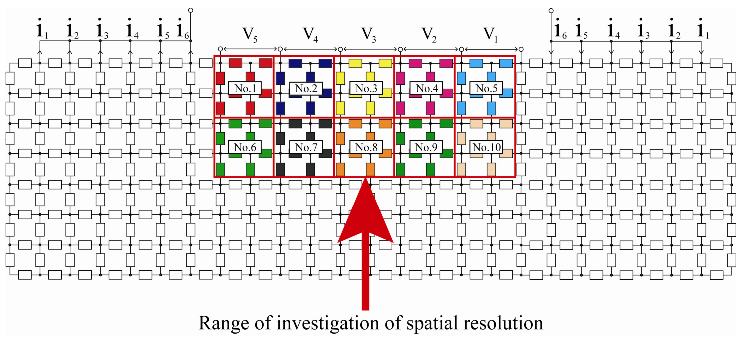

FIGURE 7: The Tissue Divided into 10 Parts.

Figure 7 shows the equivalent circuit model used for our simulations, where a tissue is divided in to 10 cells. Since each cell (or equivalent circuit) has 3 parameters, this model involves 30 parameters. The number of voltage electrodes is 5 (M) and the number of current electrodes is 6 (N). The number of measurement frequencies is 10 (K) in the range of 0 to 100[kHz] (ωi). Therefore, the number of measurement data is 5×6×10=300.

Table 1 shows the model parameters and the initial estimated parameter for the proposed novel algorithm. Alopex algorithm converges to initial parameter values such that the error is within the 10% range. The final values obtained from the Alopex algorithm are represented as the estimated parameter values in Table 1.

Parameter Values		**Re[Ω]**	**Ri[Ω]**	**Cm[nF]**
Model Parameters	No. 1	180	180	10
	No. 2	80	70	11
Initial Parameters	No. 1	0	0	0
	No. 2	0	0	0
Estimated Parameters	No. 1	174.9	161.8	6.9
	No. 2	86.0	117.7	17.6

TABLE 1: Selecting Initial Parameters through Alopex Method.

Note that here model parameter values represent the global minimum for parameter values for p. No.1 relates to the 2-D model while no.2 relates to the 3-D model. These values were obtained by actually removing the living tissue through dissection and measuring the values. The initial parameter values were set to 0 for Alopex for both models.

The estimated parameter values from Table 1 are applied as the initial parameter values for determining the final values of all the parameters as shown in Figure 6. One can clearly analyze that the output (estimated parameter) from Table 1 is the input (initial parameters) in Table 2.

Parameter Values		**Re[Ω]**	**Ri[Ω]**	**Cm[nF]**
Model Parameters	No. 1	180	180	10
	No. 2	80	70	11
Initial Parameters	No. 1	174.9	161.8	6.9
	No. 2	86.0	117.7	17.6
Estimated Parameters	No. 1	180.0	180.0	10.0
	No. 2	80.0	70.0	11.0

TABLE 2: Calculating the Final Values through Newton's Method.

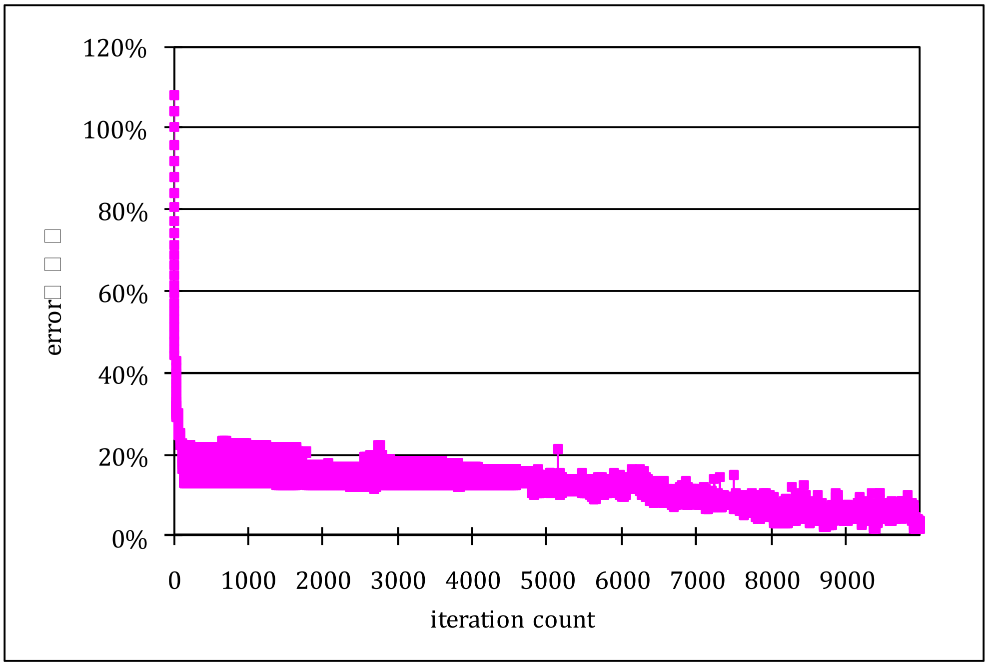

FIGURE 8: Convergence Graph Using the Alopex Algorithm.

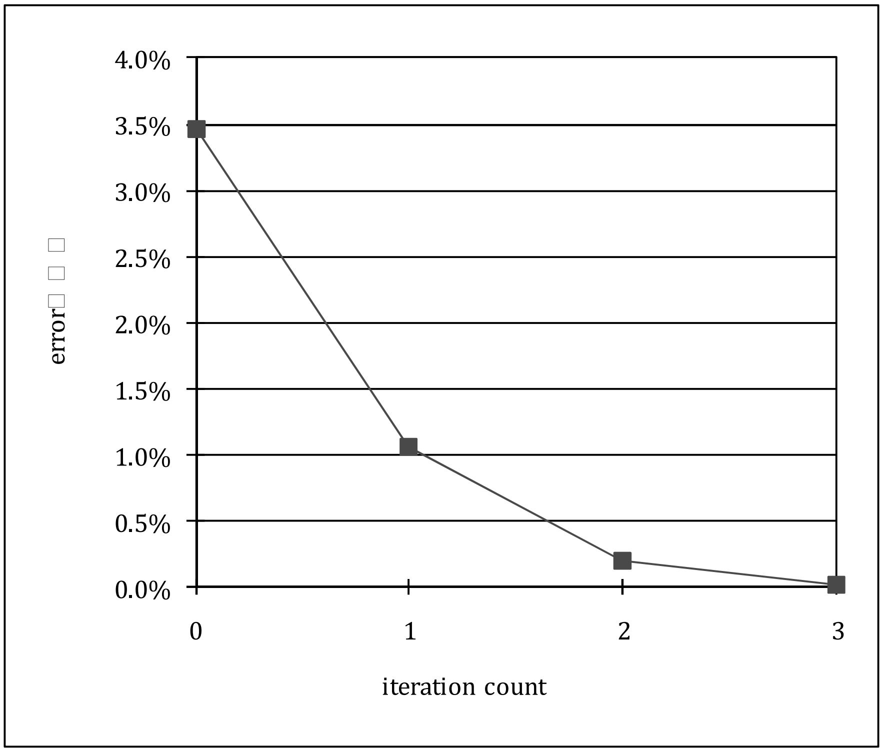

FIGURE 9: Convergence Graph Using the Proposed Novel Algorithm.

Figure 8 shows the error value as a function of iterations during the stochastic phase. Figure 9 shows the error values starting at 3.5% (ending value in Figure 8) and converging to zero within 3 iterations during the deterministic phase.

7. CONCLUSION

EIT, a non-invasive method, creates a two-dimensional image from information based on the impedance characteristics of the living tissue. In this paper a living tissue is represented by the two-dimensional equivalent circuit. The equivalent circuit is composed of intracellular and extracellular resistances Ri, Re, and cell membrane capacitance Cm which allows for modelling the non-uniformity of living tissue. The paper addresses the issue of electrode structure by using an arrangement called “divided electrode” for measurement of bio-impedance in a cross section of a local tissue. Its capability was examined by computer simulations, where a distributed equivalent circuit was utilized as a model for the cross section tissue. Further, a novel artificial intelligence based hybrid model was proposed. The proposed model ameliorates the achievement of spatial resolution of equivalent circuit model to the closest accuracy. While measuring the impedence value, it is extremely important to estimate appropriate values for all initial parameters. However, estimation of these initial parameters using Newton’s method is extremely difficult. The proposed novel algorithm which uses a combination of stochastic and deterministic approach addresses this issue. Thus, the results obtained were highly accurate.

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Classification of Churn and non-Churn Customers for Telecommunication Companies

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Abstract

Telecommunication is very important as it serves various processes, using of electronic systems to transmit messages via physical cables, telephones, or cell phones. The two main factors that affect the vitality of telecommunications are the rapid growth of modern technology and the market demand and its competition. These two factors in return create new technologies and products, which open a series of options and offers to customers, in order to satisfy their needs and requirements. However, one crucial problem that commercial companies in general and telecommunication companies in particular suffer from is a loss of valuable customers to competitors; this is called customer-churn prediction. In this paper the dynamic training technique is introduced. Dynamic training is used to improve the prediction of performance. This technique is based on two ANN network configurations to minimise the total error of the network to predict two different classes: namely churn and non-customers.

Keywords: Artificial Neural Network, Classification, Prediction, Dynamic Training, Telecommunication.

1. INTRODUCTION

The telecommunication industry is volatile and rapidly growing, in terms of the market dynamicity and competition. In return, it creates new technologies and products, which open a series of options and offers to customers in order to satisfy their needs and requirements [1, 2]. However, one crucial problem that commercial companies in general and telecommunication companies in particular suffer from is a loss of valuable customers to competitors; this is called customer-churn prediction. A customer who leaves a carrier in favor of competitor costs a carrier more than if it gained a new customer [1].

Therefore, “customer-churn prediction” can be seen as one of the most imperative problems that the telecommunication companies face in general. To tackle this problem one needs to understand the behavior of customers, and classify the churn and non-churn customers, so that the necessary decisions will be taken before the churn customers switch to a competitor. More precisely, the goal is to build up an adaptive and dynamic data-mining model in order to efficiently understand the system behavior and allow time to make the right decisions. This will also replace deficiencies of previous work and existing techniques, which are very expensive and time consuming, this problem is studied in the field of telephony with different techniques such as Hidden Markov Model [3], Gaussian and mixture and Bayesian networks [4], association rules [5] decision trees and neural networks [1].

In the last two decades, machine learning techniques [6] have been widely used in many different scientific fields.

Artificial Neural Network [7] is a very popular type of machine learning and it can be considered as another model that is based on modern mathematical concepts. Artificial neural computations are designed to carry out tasks such as pattern recognition, prediction and classification. The performance of this type of machine learning depends on the learning algorithm and the given application, the accuracy of the modeling and structure of each model. The most popular type of learning algorithm for the feed forward neural network is the back propagation algorithm.

The reason for the selection of the feed forward neural network with back propagation learning algorithm is mainly because the network is faster than some other types of network, such as a recurrent neural network. This network has a context layer which copies and stores the hidden neuron activations that can be fed along with the inputs back to the hidden neurons in an iterative manner [8]. On the one hand the context layer (memory) will add more accuracy to the network, than feed forward neural network. On the other hand the network will need more time to learn when it is fed with large training data sets and enormous input features. The feed forward neural network is used as a trade off technique to solve the customer churn and non churn prediction problem.

In the next section the architecture of the artificial neural networks is explained, and then the back propagation algorithm is outlined. Dynamic training is then introduced, after that simulation and results are presented, and finally the main points are concluded.

2. METHODS: NEURAL NETWORK ARCHITECTURE

A standard feed forward ANN architecture is used in this paper. This is a fully connected feed forward neural network also called Multi Layer Perceptron (MLP). The network has three layers input, hidden, and output as shown in Fig 1.

For supervised learning networks, there are several learning techniques that are widely used by researchers. The main three are: real time, back propagation, and back propagation through time, back propagation being what is used here [8, 9, 10] in this paper depending on the application.

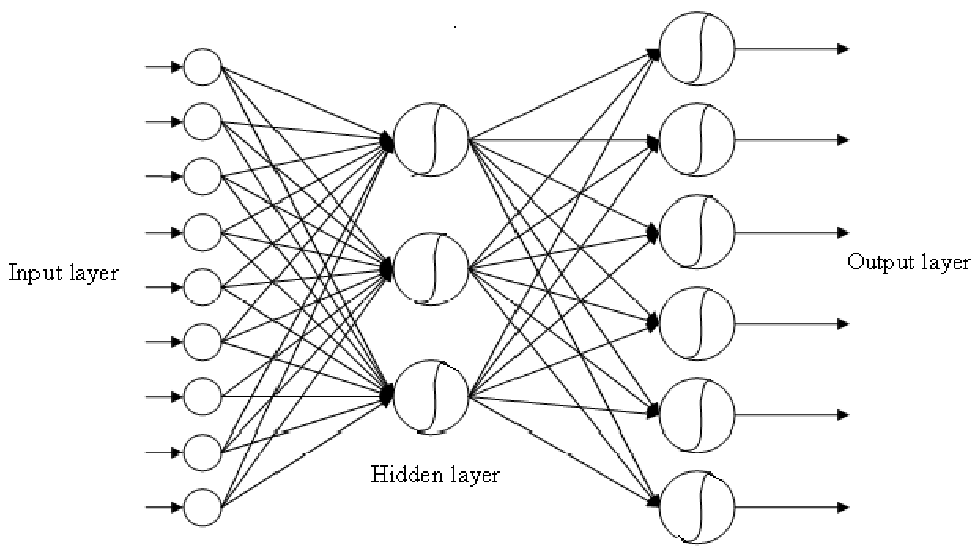

FIGURE 1: Standard feed forward neural network.

3. LEARNING ALGORITHM: BACK PROPAGATION

The back propagation (BP) algorithm is an example of supervised learning [9, 10]. It is based on the minimization of error by gradient descent. A new network is trained with BP. When a target output pattern exists, the actual output pattern is computed. The gradient descent acts to adjust each weight in the layers to reduce the error between the target and actual output patterns. The adjustment of the weights is collected for all patterns and finally the weights are updated.

The sigmoid function is used to compute the output neurons as in equation (1).

$$f(x) = \frac{1}{(1+e^{-x})} \qquad (1)$$

Where x represents the net input, the derivative of activation function is

$$f(x) = (1 - f(x))f(x) \qquad (2)$$

The back propagation pass will find the difference between the target and actual output in the output layer

$$e_k = d_k - O_k \qquad (3)$$

Where d_k and O_k are the desired and actual outputs for neuron k.
Backpropagation learning defines the sum of error

$$E = \sum_{example=1}^{P} \frac{1}{2} \sum_{k \in outputs} (d_k - O_k)^2 \qquad (4)$$

For the output layer, the local gradient is calculated as follows:

$$\delta_k = e_k\ O_k\ (1 - O_k) \qquad (5)$$

For the hidden layer, the local gradient is calculated as follows:

$$\delta_j = O_j(1 - O_j) \sum_k \delta_k w_{kj} \qquad (6)$$

The network learning algorithm adjusts the weights by using delta rule [9, 10], by calculating the local gradients.

$$\Delta w_{jk}^{new} = \mu \Delta w_{jk}^{old} + \beta \delta O_k \qquad (7)$$

$$w_{jk}^{new} = w_{jk}^{old} + \Delta w_{jk}^{new} \qquad (8)$$

When new is the current iteration and old is the previous iteration. β is learning rate (0.009-0.9999), μ is momentum constant.

4. DYNAMIC TRAINING

Dynamic training is introduced and used to improve the prediction performance of the classifiers. This technique is based on two ANN network configurations. The first network is large and uses the whole training set. After the training is done, a random portion from the training set is taken as a testing set and presented to the network. The forecasting results of that portion are re-organized and used as input patterns with their original targets from the trainings and then used to train the second network; a smaller network. The termination of the learning phases is based on the specified threshold error. Then for testing, the data of the required predicted data is presented to the smaller network. The results of the larger network are reorganized in two inputs to be presented to the smaller network. Bear in mind that the larger network structure will have 124-40-2 (124 input neurons, 40 neurons hidden neurons, 2 output neurons). The smaller network configuration consists of 2–6-2.

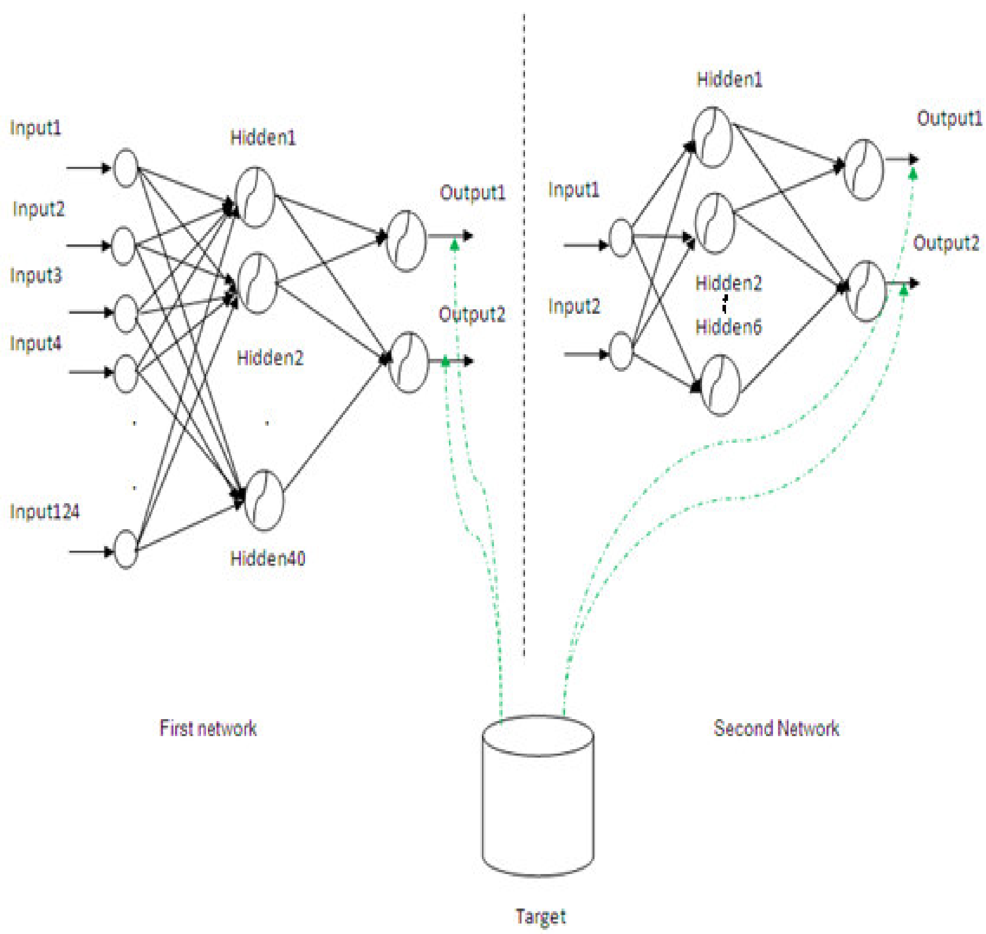

FIGURE 2: Figure displays dynamic training.

5. IMPLEMENTATION AND RESULTS

The prediction system can be processed as follows: obtain and analyze the historical data; pre-processing and normalizing information; choosing the training and testing set; choosing the type of network and its parameters; choosing a suitable learning algorithm; and finally implementation.

The prediction task mainly depends on the training and testing data sets. The size of data selected was 13,000 samples out of a total 1,500,000 customers as neural networks have the ability to learn and generalize.

The training and testing data sets were selected to perform the historical data. Given the nature of our generic selection for the training set, our system is in fact able to predict any random 1000 customers that are not trained and seen by the network (see Table 1).

Population: Number of customers	Size of the samples	Training set	Test set
1,500,000	13000	4000 customers	1000 customers

TABLE 1: Table displays the size of the historical data, training and testing patterns.

There are a lot of important features that have been taken into consideration. These features are related to the customers of telecommunication in the historical data. The main features are the customer's contact data and details, customer behaviors and calls, customer's request for services, etc. The number of input features to the network was 124. And the number of the output features is 2. The input features are scaled down, normalized and transformed. The transformation involves manipulating the data input to create a single input to a neural network, whereas the normalization is a conversion performed on a single data input to scale the data into a suitable range for the neural network. Therefore there is no need to use binary code for the input data. Furthermore there isn't a strong trend in the data. All input data features are linearly scaled and within the range of all variables which are chosen (between 0 and 1).

The number of output features is 2. The output pattern is organized in binary code as 0 1 which represents churn customer and 1 0 represents non-churn customers (see Table 2).

Churn customer	Non-churn customer
0 1	1 0

TABLE 2: displays output feature.

Two different network structures were used with different parameters for both feed forward networks. A generic model was selected to include all the data. The first network structure was consisted of 124-40-2 (124 input neurons, 40 hidden neurons, and 2 outputs), whereas the second network structure has two networks, as explained in section 5; the large network was 124-40-2 and the small was 2-6-2. The hidden layer neurons were selected based on trial and error and in tandem with each structure with each network (40 hidden neurons for the larger structure and 6 hidden neurons for the smaller network structure). Each network structure used relatively different network parameters. These parameters relied heavily on the size of training and testing sets. Learning rates and momentum were varied. The training cycles were also varied. The type of activation function was a logistic function for the hidden layer and linear for output layer. For the ANN structures patterns of training data were trained and presented to the network in cycles. After every cycle, the weight connection was modified and updated automatically. The processes were iterative. It is important to mention that a specific value of tolerance should be declared to stop training. This threshold was chosen so that it ensured the model fitted to the training data, and it also did not guarantee good out-of-sample performance. The results with the first network with dynamic training technique was better than the standard technique, the matrix confusion and matrix rate [11] for both networks were shown. Table 3 displays classification for the predicted values for both churn and non churn classes against the actual target of the testing set. It also shows the matrix rate for prediction values for both churn and non-churn values against the actual values. Likewise Table 4 shows results for the standard network structure. As can be seen from Tables 3 and 4, clear misclassifications, in other words, 13 samples of churn class were misclassified and categorized as non-churn samples by the network as seen in Table 3. The likewise with Table 4, 16 samples of churn class were misclassified and categorized as non-churn class. We believe the reason behind this type of misclassification is the misrepresentation of our training and testing data; in other words, the imbalance of data sets caused this problem [11, 12, 13, 14]: as we have in our training set, the number of non-churn class is 3782, and churn class is only 218, and in the testing data set, the number of sample of non-churns 63, and the number of non-churn class is 937. The difference in the results as shown in Table 3 and 4 is small enough to be not essential. Nevertheless, these results for our relatively large sample of data are statistically significant.

matrix confusion		
	Actual	
Predicted	Churn	Non-Churn
Churn	50	13
Non-Churn	0.0	937
matrix rate		
	Actual	
Predicted	Non-churn	Churn
non-Churn	0.7936	0.2063
Churn	0.0	1.0

TABLE 3: Displays matrix confusion and matrix rate for the standard network with dynamic training.

matrix confusion		
	Actual	
Predicted	Churn	Non-Churn
Churn	47.0	16.0
Non-Churn	0.0	937.0

matrix rate		
	Actual	
Predicted	Non-churn	Churn
non-Churn	0.7460	0.2539
Churn	0.0	1.0

TABLE 4: Displays matrix confusion and matrix rate for the standard neural network.

6 CONCLUSION

This paper deals with the problem of classification of churn and non-churn customers in telecommunication companies. Telecommunication is very important as it provides various services of electronic systems to transmit messages through telecommunication devices. However, one crucial problem that commercial companies in general and telecommunication in particular suffer from is a loss of valuable customers to competitors; this is called customer-churn prediction. Machine learning techniques have been widely applied to solve various problems. These machines have been showing great results in many applications. Artificial neural network with the back propagation learning algorithm is used [7, 9, 10, 15, 16, 17]. Variant structures of neural network are discussed. The dynamic training technique is also introduced in this paper. It is used to improve the performance of prediction of the two classes, namely churn and non-churn customers. This technique is based on two ANN network configurations to minimize the total error of the network to predict two different types of customers. The artificial neural network with dynamic training performed better than just an artificial neural network alone. The difference in the results as shown in Table 3 and 4 is small enough to be not essential. However, these results for our relatively large sample of data are statistically significant.

Software in Java language is implemented and used to compute the confusion and rate matrices. The results are presented. As can be seen from our results, both networks showed clear misclassifications. We believe the reason behind this type of misclassification is the misrepresentation of our training and testing data. In other words, the imbalanced training and testing data sets caused this problem. Therefore, further research work should be carried out in order to tackle the misrepresentation of the historical data and to improve the dynamic training technique.

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Review of Multimodal Biometrics: Applications, challenges and Research Areas

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Abstract

Biometric systems for today's high security applications must meet stringent performance requirements. The fusion of multiple biometrics helps to minimize the system error rates. Fusion methods include processing biometric modalities sequentially until an acceptable match is obtained. More sophisticated methods combine scores from separate classifiers for each modality. This paper is an overview of multimodal biometrics, challenges in the progress of multimodal biometrics, the main research areas and its applications to develop the security system for high security areas.

Keywords: Multimodal, biometrics, feature extraction, spoofing.

1. INTRODUCTION

Biometrics refers to the physiological or behavioral characteristics of a person to authenticate his/her identity [1]. The increasing demand of enhanced security systems has led to an unprecedented interest in biometric based person authentication system. Biometric systems based on single source of information are called unimodal systems. Although some unimodal systems [2] have got considerable improvement in reliability and accuracy, they often suffer from enrollment problems due to non-universal biometrics traits, susceptibility to biometric spoofing or insufficient accuracy caused by noisy data [3].

Hence, single biometric may not be able to achieve the desired performance requirement in real world applications. One of the methods to overcome these problems is to make use of multimodal biometric authentication systems, which combine information from multiple modalities to arrive at a decision. Studies have demonstrated that multimodal biometric systems can achieve better performance compared with unimodal systems.

This paper presents the review of multimodal biometrics. This includes applications, challenges and areas of research in multimodal biometrics. The different fusion techniques of multimodal biometrics have been discussed. The paper is organized as follows. Multi algorithm and multi sample approach is discussed in Section 2 whereas need of multimodal biometrics is illustrated in Section 3, the review of related work, different fusion techniques are presented in Section 4. Applications, challenges and research areas are given in Section 5 and Section 6 respectively. Conclusions are presented in the last section of the paper.

2. MULTI ALGORITHM AND MULTI SAMPLE APPROACH

Multi algorithm approach employs a single biometric sample acquired from single sensor. Two or more different algorithms process this acquired sample. The individual results are combined to obtain an overall recognition result. This approach is attractive, both from an application and research point of view because of use of single sensor reducing data acquisition cost. The 2002 Face Recognition Vendor Test has shown increased performance in 2D face recognition by combining the results of different commercial recognition systems [4]. Gokberk et al. [5] have combined multiple algorithms for 3D face recognition. Xu et al. [6] have also combined different algorithmic approaches for 3D face recognition.

Multi sample or multi instance algorithms use multiple samples of the same biometric. The same algorithm processes each of the samples and the individual results are fused to obtain an overall recognition result. In comparison to the multi algorithm approach, multi sample has advantage that using multiple samples may overcome poor performance due to one sample that has unfortunate properties. Acquiring multiple samples requires either multiple copies of the sensor or the user availability for a longer period of time. Compared to multi algorithm, multi sample seems to require either higher expense for sensors, greater cooperation from the user, or a combination of both. For example, Chang et al. [7] used a multi-sample approach with 2D face images as a baseline against which to compare the performance of multi-sample 2D + 3D face.

3. NEED OF MULTIMODAL BIOMETRICS

Most of the biometric systems deployed in real world applications are unimodal which rely on the evidence of single source of information for authentication (e.g. fingerprint, face, voice etc.). These systems are vulnerable to variety of problems such as noisy data, intra-class variations, inter-class similarities, non-universality and spoofing. It leads to considerably high false acceptance rate (FAR) and false rejection rate (FRR), limited discrimination capability, upper bound in performance and lack of permanence [8]. Some of the limitations imposed by unimodal biometric systems can be overcome by including multiple sources of information for establishing identity. These systems allow the integration of two or more types of biometric systems known as multimodal biometric systems. These systems are more reliable due to the presence of multiple, independent biometrics [9]. These systems are able to meet the stringent performance requirements imposed by various applications. They address the problem of non-universality, since multiple traits ensure sufficient population coverage. They also deter spoofing since it would be difficult for an impostor to spoof multiple biometric traits of a genuine user simultaneously. Furthermore, they can facilitate a challenge – response type of mechanism by requesting the user to present a random subset of biometric traits thereby ensuring that a ‘live’ user is indeed present at the point of data acquisition.

4. MULTIMODAL BIOMETRICS

The term “multimodal” is used to combine two or more different biometric sources of a person (like face and fingerprint) sensed by different sensors. Two different properties (like infrared and reflected light of the same biometric source, 3D shape and reflected light of the same source sensed by the same sensor) of the same biometric can also be combined. In orthogonal multimodal biometrics, different biometrics (like face and fingerprint) are involved with little or no interaction between the individual biometric whereas independent multimodal biometrics processes individual biometric independently. Orthogonal biometrics are processed independently by necessity but when the biometric source is the same and different properties are sensed, then the processing may be independent, but there is at least the potential for gains in performance through collaborative processing. In collaborative multimodal biometrics the processing of one biometric is influenced by the result of another biometric.

A generic biometric system has sensor module to capture the trait, feature extraction module to process the data to extract a feature set that yields compact representation of the trait, classifier module to compare the extracted feature set with reference database to generate matching scores and decision module to determine an identity or validate a claimed identity. In multimodal biometric system information reconciliation can occur at the data or feature level, at the match score level generated by multiple classifiers pertaining to different modalities and at the decision level.

Biometric systems that integrate information at an early stage of processing are believed to be more effective than those which perform integration at a later stage. Since the feature set contains more information about the input biometric data than the matching score or the output decision of a matcher, fusion at the feature level is expected to provide better recognition results. However, fusion at this level is difficult to achieve in practice because the feature sets of the various modalities may not be compatible and most of the commercial biometric systems do not provide access to the feature sets which they use. Fusion at the decision level is considered to be rigid due to the availability of limited information. Thus, fusion at the match score level is usually preferred, as it is relatively easy to access and combine the scores presented by the different modalities [1].

Rukhin and Malioutov [10] proposed fusion based on a minimum distance method for combining rankings from several biometric algorithms. Fusion methods were compared by Kittler et al. [11], Verlinde et al. [12] and Fierrez-Aguilar et al. [13]. Kittler found that the sum rule outperformed many other methods, while Fierrez-Aguilar et al. [13, 14] and Gutschoven and Verlinde [15] designed learning based strategies using support vector machines. Researchers have also investigated the use of quality metrics to further improve the performance [16, 14, 17–21].

Many of these techniques require the scores for different modalities (or classifiers) to be normalized before being fused and develop weights for combining normalized scores. Normalization and quality weighting schemes involve assumptions that limit the applicability of the technique. In [22], Bayesian belief network (BBN) based architecture for biometric fusion applications is proposed. Bayesian networks provide united probabilistic framework for optimal information fusion. Although Bayesian methods have been used in biometrics [16, 23–25], the power and flexibility of the BBN has not been fully exploited.

Brunelli et al. [26] used the face and voice traits of an individual for identification. A Hyper BF network is used to combine the normalized scores of five different classifiers operating on the voice and face feature sets. Bigun et al. [16] developed a statistical framework based on Bayesian statistics to integrate the speech (text dependent) and face data of a user [27]. The estimated biases of each classifier are taken into account during the fusion process. Hong and Jain associate different confidence measures with the individual matchers when integrating the face and fingerprint traits of a user [28]. They also suggest an indexing mechanism wherein face information is used to retrieve a set of possible identities and the fingerprint information is then used to select a single identity. A commercial product called BioID [29] uses the voice, lip motion and face features of a user to verify the identity. Aloysius George used Linear Discriminant analysis (LDA) for face recognition and Directional filter bank (DFB) for fingerprint matching. Based on experimental results, the proposed system reduces FAR down to 0.0000121%, which overcomes the limitation of single biometric system and proves stable personal verification in real-time [30].

5. APPLICATIONS

The defense and intelligence communities require automated methods capable of rapidly determining an individual's true identity as well as any previously used identities and past activities, over a geospatial continuum from set of acquired data. A homeland security and law enforcement community require technologies to secure the borders and to identify criminals in the civilian law enforcement environment. Key applications include border management, interface for criminal and civil applications, and first responder verification.

Enterprise solutions require the oversight of people, processes and technologies. Network infrastructure has become essential to functions of business, government, and web based business models. Consequently securing access to these systems and ensuring one's identity is essential. Personal information and Business transactions require fraud prevent solutions that increase security and are cost effective and user friendly. Key application areas include customer verification at physical point of sale, online customer verification etc.

6. CHALLENGES AND RESEARCH AREAS

Based on applications and facts presented in the previous sections, followings are the challenges in designing the multi modal systems. Successful pursuit of these biometric challenges will generate significant advances to improve safety and security in future missions. The sensors used for acquiring the data should show consistency in performance under variety of operational environment. Fundamental understanding of biometric technologies, operational requirements and privacy principles to enable beneficial public debate on where and how biometrics systems should be used, embed privacy functionality into every layer of architecture, protective solutions that meet operational needs, enhance public confidence in biometric technology and safeguard personal information.

Designing biometric sensors, which automatically recognize the operating environment (outdoor / indoor / lighting etc) and communicate with other system components to automatically adjust settings to deliver optimal data, is also the challenging area. The sensor should be fast in collecting quality images from a distance and should have low cost with no failures to enroll [IJBB5].

The multimodal biometric systems can be improved by enhancing matching algorithms, integration of multiple sensors, analysis of the scalability of biometric systems, followed by research on scalability improvements and quality measures to assist decision making in matching process. Open standards for biometric data interchange formats, file formats, applications interfaces, implementation agreements, testing methodology, adoption of standards based solutions, guidelines for auditing biometric systems and records and framework for integration of privacy principles are the possible research areas in the field.

7. CONCLUSIONS

This paper presented the various issues related to multimodal biometric systems. By combining multiple sources of information, the improvement in the performance of biometric system is attained. Various fusion levels and scenarios of multimodal systems are discussed. Fusion at the match score level is the most popular due to the ease in accessing and consolidating matching scores. Performance gain is pronounced when uncorrelated traits are used in a multimodal system. The challenges faced by multimodal biometric system and possible research areas are also discussed in the paper.

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